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A Real Options Perspective on R&D Portfolio Diversification

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Abstract

This paper shows that the presence of conditional staging in R&D (Research & Development) has a critical impact on portfolio risk, and changes diversification arguments when a portfolio is constructed. When R&D projects exhibit option-like characteristics, correlation between projects plays a more complicated role than traditional portfolio diversification would suggest. Real option theory argues that research projects with conditional phases have option-like risk and return properties, and are different from unconditional projects. We show that although the risk of a portfolio always depends on the correlation between projects, a portfolio of conditional R&D projects with real option characteristics has fundamentally different risk than a portfolio of unconditional projects. When conditional R&D projects are negatively correlated, portfolio risk is hardly reduced by diversification. When projects are positively correlated, however, diversification is more effective than these tools predict.

Key words: Real Options; Research & Development (R&D); Risk Management; Monte Carlo

1 Introduction

If the outcomes of a firm's endeavors are unknown, a key strategy to deal with such risk is betting on more than one horse. Successful R&D policy therefore requires the selection and development of several concurrent alternatives, known as diversification. Additionally, in order to timely abandon unprofitable projects, R&D management often involves breaking an individual R&D project into stages, so that certain requirements must be met before it can enter the next development phase. The sequential nature then brings conditionality to the project and causes R&D projects to exhibit option-like behavior, which complicates the diversification argument. This paper examines diversification when conditional staging is present in an R&D portfolio, and shows that reliance on traditional diversification arguments can be quite misleading. As compared to diversification of traditional (unconditional) projects, conditionally staged projects are less sensitive to changes in correlation and risk is therefore more difficult to diversify. Our results show that negative correlation amongst conditionally staged projects makes diversification a less effective instrument to eliminate risk than for unconditional projects. Positive correlation amongst conditionally staged projects, however, makes diversification more effective.

Real options analysis has become a well-established R&D project valuation technique for intertemporal risky investments in R&D. Rooted in financial theory, Myers (1977) was the first to describe real options as "the opportunities to purchase real assets on possibly favorable terms". In their seminal paper, Black and Scholes (1973) consider equity of a real, levered firm as an option on its

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entity value. In the strategy literature, Bowman and Hurry (1993) and Bettis and Hitt (1995) propose real options theory as an alternative lens for looking at technology investments that closely resemble the behavior and characteristics of real options. In the R&D literature, Thomke (1997) indeed shows empirically that flexibility under uncertainty allows firms to continuously adapt to change and improve products. Hartmann and Hassan (2006) provide empirical evidence that real option analysis is used as an auxiliary valuation tool [1] in pharmaceutical project valuation. In this context, a basic implementation is provided by Kellogg and Charnes (2000), and more sophisticated option valuation models for pharmaceutical research have been developed by Loch and Bode-Greuel (2001). Lee and Paxson (2001) view the R&D process and subsequent discoveries as sequential (compound) exchange options. Cassimon et al. (2004) provide an analytical model to value the phased development of a pharmaceutical R&D project. The empirical literature also confirms that R&D yields the positively skewed distribution of returns that is typical for options. For instance, Scherer & Harhoff (2000) show that the top 10% of the investigated inventions and innovations captured 48 to 93 percent of total sample returns. They refer to Nordhaus (1989), who postulates that 99.99% of the tens of thousands of invention patents issued each year are worthless, but that the remaining 0.01% have high values.

[1] The fundamental difference between real options and traditional Discounted Cash Flow (DCF) valuation lies in the flexibility to adapt when circumstances change. Whereas DCF valuation fixes an investment decision once and for all, an option is the right (not the obligation) to invest in R&D at some future date. If future circumstances are favorable, the option will be exercised; if not, the option will expire without any further cost. Such freedom of choice enables an investor to timely abandon the project so that further losses are avoided. Therefore, many unfavorable investments (with limited downside risk) can be financed by a few highly profitable investments (with unlimited upside potential). Profitable investments will account for the majority of returns, so the return distribution becomes positively skewed.

In concurrence with these findings, we analyze conditionally staged (unconditional) projects as financial options (equity shares). Such R&D typically has a high (low) chance of failure and can be deemed risky (low-risk). High-risk projects in R&D are by and large of an explorative nature: examples are basic and fundamental research, or R&D in response to (or in anticipation of) important changes in a firm's strategic environment. Low-risk projects in R&D are most often of an incremental nature: examples are 'me-too' inventions that imitate a successful competitor's invention, or investments in (or variations of, or incremental changes to) an already commercialized product. We will refer to these projects by conditionally staged and unconditional projects, respectively.

Although most real options studies have primarily examined projects in isolation, Engwall (2003) argues that every project takes off from, or is executed in, an organizational context. Real options should therefore also be considered as part of a portfolio. Brosch (2001) contemplates on the influence of interacting real options *within* projects. These positive and negative interactions between options make a portfolio's value non-additive. Our focus, however, is on option interactions *between* projects, and we focus on the risk of the portfolio. Smith and Thompson (2003, 2005) postulate a project selection strategy in sequential petroleum exploration, where the outcome of the prior drillings can be observed before investing in the next drilling. We are also involved with real option selection, but focus on simultaneous (non-sequential) development. Multiple assets have been examined by Wörner et al. (2002, 2003), who describe a firm that conducts several R&D projects as a 'basket option', or an option on a set of stochastic variables. Yet, as they focus on the value of a single claim that pertains to many random variables, their analysis does not derive results for portfolio management (which inherently deals with the

selection between multiple claims). In our argument below, we examine conditional projects (or firms) and how their individual risk- and return properties affect the overall risk of a portfolio.

When constructing an R&D portfolio, the selection of candidates comprises many important, non-monetary considerations: for example, Prencipe and Tell (2001) show that firms try to capture synergies that stem from learning processes. Several studies have therefore aimed to integrate risk diversification with expected costs and benefits, inter-project synergies, externalities, R&D quality and overall fit with the business strategy. In this tradition, Linton, Walsh, and Morabito (2002) developed a framework that combines both quantitative and qualitative measures to rank and select the projects in a portfolio. Furthermore, Martino (1995) describes several methods for R&D project selection including cluster analysis, cognitive modeling, simulation, portfolio optimization, and decision theory. While these sources are suitable for handling technical and physical diversification, they seem less appropriate for allocating financial resources than the Markowitz (1952) diversification argument. Markowitz's principle is to minimize risk given a return, or vice versa. Chien (2002) includes a survey of selection procedures and shows that several originated from Markowitz's work [2]. Unfortunately, Markowitz diversification only works when the distribution of project returns is symmetric; an assumption that is violated for R&D projects with conditionality. Our argument supplements the Markowitz criterion in that it explicitly considers real option characteristics [3].

Using a portfolio of two investment opportunities, we show that although the

[2] A recent R&D selection model that is based on Markowitz's can be found in Ringuest et al. (2004).
[3] By simulating many real options, we create a skewed distribution.

risk of an R&D portfolio always depends on the correlation between projects, the dependence differs between conditional projects with real options and unconditional projects. In particular, we find that when projects are positively correlated, the overall portfolio risk for conditional projects is lower than for unconditional projects. Diversification is an important argument to motivate a portfolio of such projects, because it is more effective than one would expect from unconditional investments. When, in contrast, projects are negatively correlated, we find that the overall portfolio risk for conditional projects is higher than for unconditional projects. Moreover, under negative correlation, portfolio risk is less sensitive to changes in correlation as compared to unconditional investment projects. Diversification is therefore less effective than one would initially expect from unconditional investments, and more weight should be placed on non-diversification arguments to motivate a portfolio of such projects, such as synergies and spillovers.

Our results are relevant for public policy to allocate resources and effectively spur innovation [4]: the risk of a group of positively correlated start-ups [5] is lower than one would expect if conditionality is ignored. Hence, diversification may still be a good argument for grouping innovative companies, as risk is more effectively reduced than within industries with a more stable cash flow. At the same time, our results are relevant to the investment portfolio of a single firm: when positively correlated projects are still young and in the R&D phase, a portfolio consisting of such projects is less risky than one would expect.

[4] For instance, a (regional or federal) government may want to develop a geographical region, or stimulate research in a certain area. Does a government want to focus in order to create a specialized technology area such as Silicon Valley, or does it want to diversify in order to prevent overdependence on a few industries such as construction and car manufacturing in Detroit?

[5] Especially in an innovative field, a start-up is a risky business, often with option characteristics.

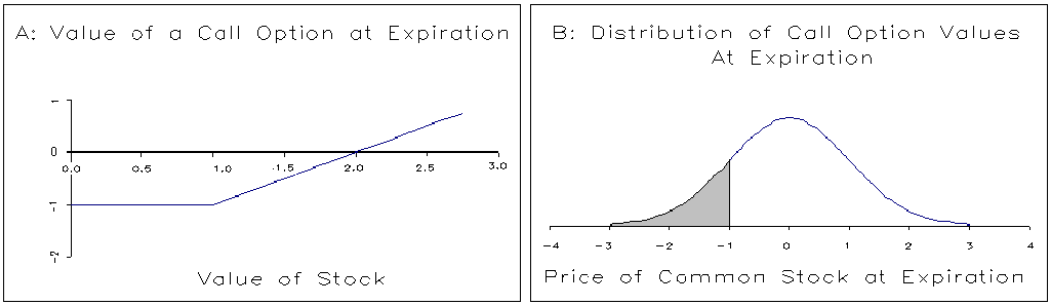
But as successful projects mature, uncertainty resolves over time, and option characteristics become less relevant, the same correlation between projects leads to more risk. To minimize overall portfolio risk, some of the matured projects may therefore be sold in exchange for negatively correlated projects with low-risk.

This paper is organized as follows: in Section 2, the theory behind a portfolio of real options is conveyed. In Section 3 we present the model and its results, and answer the question why pharmaceutical firms focus instead of diversify by using our model. In Section 4, we discuss managerial implications and conclude. In the Appendices A and C, a proof of our findings is provided, as well as a means to extend our analysis to a more realistic setting.

2 Conceptual Framework

An opportunity to invest can turn out favorably or unfavorably. In the first case the investor makes a profit, and otherwise he looses no more than the initial amount invested. Such limited liability causes the investor's payoff structure to be non-linear, and further investment is conditional on a positive value development in the future. This is the key characteristic of a financial option. The familiar payoff structure of both the investor and an individual European option at maturity is shown in Figure 1A: if the stock is valued at less than the investment (equal to \$1) , the call is worthless. The exercise price is analogous to the present value of the investment that is made after the initial investment to acquire the option. If the stock price is larger than \$1, its value rises one-to-one with increases in the stock price. The stock price is analogous

Figure 1. Return on an individual call option and on a population of call options
Consider the following call option: each option costs 1$ in exchange for the right (not the obligation) to buy the common stock at a fixed price, here being also 1$. The individual option is worthless when the price of the stock is 1$ or below. The distribution of option returns is truncated: any return value below -1$ is impossible. Figure 1a shows the value of a single call option at expiration. Figure 1b shows the return distribution of a population of call option returns, where the shaded part is truncated.



to the present value of the project's cash flows [6]. So at expiration the project value can either be zero, or larger than zero.

Figure 1B shows what this means for a large portfolio of calls, which is a valid way to describe reality if the portfolio's constituents behave similar to financial options, i.e., if a portfolio consists entirely of conditionally staged projects as often found in pharmaceuticals, biotechnology, venture capital and software technology. Since negative values are impossible to obtain, a distribution of returns that would otherwise be normal now becomes truncated from the left: when the underlying stock is not worth the exercise price, the option will remain unexercised. Therefore, the shaded area of the distribution is nonexistent and the distribution seizes to be symmetrical [7].

[6] The analogy holds also for the other variables that are needed to calculate the value of an option: the variance of stock is analogous to the project's cash flow volatility, and the time to maturity is analogous to the investor's time available to defer a next investment. The risk-free rate represents the time value of money in both the real and financial setting.

[7] Because the value of a project is a random variable and the option value on the project is a convex function of the project value, it is known that

$$E[OV(x)] > OV(E[x])$$

If the projects are without conditional staging, the shaded area would exist, the distribution would be symmetrical and by a 'perfect hedge', a riskless portfolio can be created: when two equity shares are perfectly negatively correlated, one goes down by an equal amount if the other goes up and vice versa [8], so that all deviation is offset. In line with Markowitz (1952), we call this hedging mechanism the "diversification effect" on the risk of a portfolio. However, if the projects are conditionally staged, project values are option-like distributed, above-average returns are no longer offset by below-average returns and Markowitz's (1952) diversification principle is no longer valid. Because the payoff from a call cannot fall below zero, the option already provides insurance against the negative payoffs by nullifying those payoffs that are lower than the exercise price. As a consequence, these would-be-negative payoffs are no longer available for diversification, and constructing a riskless portfolio is no longer possible. In a portfolio of options, paradoxically, the key characteristic of an option limits downside risk of the individual project, but complicates diversification and increases risk of the portfolio. In line with Jensen's Inequality, we call this the 'convexity effect', which may partly offset the diversification effect. In Appendix A, we derive this result as we examine the variance of a conditionally staged portfolio more explicitly.

In the next section, we will develop a Monte Carlo simulation model to show the effect of risky projects on a portfolio of R&D projects. The procedure is straightforward and can easily be used in practice with other portfolio selection criteria. But before we proceed, a proper definition of the key concepts is

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where OV is the value of the option and x is the project value. In this particular case, this means that the expected value of the option on the project is larger than an option on the expected value of the project. This inequality is known as Jensen's Inequality, and is caused by the nonlinear transformation of an option value on some underlying asset.

[8] That is, when uncertainty is constant and equal for both shares.

appropriate. This paper is focused on the risk of a portfolio, and is therefore a supplement to other portfolio selection criteria we already mentioned. Their importance notwithstanding, for the sake of argument we group all these criteria under the name of "non-diversification criteria". The "uncertainty" in our portfolio is completely determined by how the market value of projects develops: we confine our analysis to the relation between market values of projects, and assume the project costs to be independent and known. We prefer this setup because modelling more than one uncertainty would cause our results to become confounded. For more realistic settings, the procedure can be easily extended to accommodate two or more related stochastic processes such as uncertain costs and benefits.

3 Methodology and Results

3.1 Simulation Model

To find the volatility of an option portfolio, we need to estimate the volatility of payoffs for each option. The payoffs can be found by examining the lognormal value distribution of market prices for R&D projects, which are assumed to follow a geometric Brownian motion.

We start with two projects $i\epsilon\{1,2\}$. Unless we consider the special cases in Appendix A, it is not possible to determine the risk of an option portfolio analytically because the joint distribution of options is not analytically tractable. We therefore model the behavior of both end-of-R&D values projects V_i by a simple normal distribution [9], defined as follows:

[9] Our results also persist for other models of behavior.

$$V_i = \mu_i + \sigma_i \varepsilon_i \tag{1}$$

where μ_i is the project value, σ_i is the standard deviation of project values and ε_i is a random draw from a standard normal distribution. For each project i, we calculate the option value OV_i:

$$OV_i = \max[V_i - X_i, 0]e^{-rT} \tag{2}$$

where X_i is the investment, needed to start or acquire the project. To find the volatility of an option, we repeat equations 1 and 2 R times and see how its values are distributed:

$$\sigma_{OV_i} = \sqrt{\frac{1}{R}\sum_r (OV_{ir} - \overline{OV_i})^2} \tag{3}$$

When both projects are technically related, samples need to be drawn from a bivariate standard normal distribution and the relatedness between market values is measured by means of a correlation coefficient ρ_{12} between ε_1 and ε_2. Hull (2006) describes how a bivariate standardized normal distribution can be constructed through Cholesky decomposition. For each simulation round, independent samples y_1 and y_2 are taken from a univariate standardized normal distribution and the correlated samples $\varepsilon_1$and $\varepsilon_2$are calculated as follows:

$$\varepsilon_1 = y_1 \tag{4}$$

$$\varepsilon_2 = \rho_{12} y_1 + y_2 \sqrt{1 - \rho_{12}^2} \tag{5}$$

From one set of independent samples y_1 and y_2, we generate 21 pairs of corre-

lated samples ε_1 and ε_2 (ranging from $\rho_{12} = -1.0$ to $\rho_{12} = 1.0$ with step size 0.10) by plugging in the independent sample values in equations 4 and 5 [10]. Because the value of a portfolio is simply the sum of the projects i,

$$pf = \sum_i OV_i, \tag{6}$$

the risk of the portfolio can be defined for each correlated sample $\varepsilon_1$and ε_2, similar to the variance of the option value. An estimate of this variance is based on a simulation of portfolios and averaging over R:

$$\hat{\sigma}_{pf=}\sqrt{\frac{1}{R}\sum_r (pf_r - \overline{pf})^2}. \tag{7}$$

3.2 Simulation Results

Figure 2 compares the cumulative variance of two unrelated, but otherwise identical options (i.e. equation 3, the dotted line $\sigma_0^2 = \sigma_1^2 + \sigma_2^2$ where $\rho_{12} = 0$) with 21 option pairs, which are related to a greater or less degree (i.e. equation 7, the solid, curved line). We observe that at $\rho = 0$, the variance of the option portfolio (the solid line σ_{pf}^2) is equal to the risk of the two unrelated projects σ_0^2: a portfolio of completely unrelated options is identical to options that are both separate and unrelated. In this situation, the projects are identical in value and in risk.

To illustrate the difference between the actual portfolio risk and the calculated

[10] Usually, a triangular matrix needs to be constructed that represents a consistent variance-covariance matrix (VCV). In the two-variable case, however, this is not necessary because any correlation structure between two variables is consistent as long as the correlation is between -1 and 1.

risk when using Markowitz, we have added a third, dashed line $\tilde{\sigma}^2_{pf}$ that shows the variance of the projects if we assume Markowitz diversification to be valid. This would be appropriate if the separate projects would be unconditional and behave as equity shares. To construct the three lines, the following well-known formula to calculate portfolio variance is used:

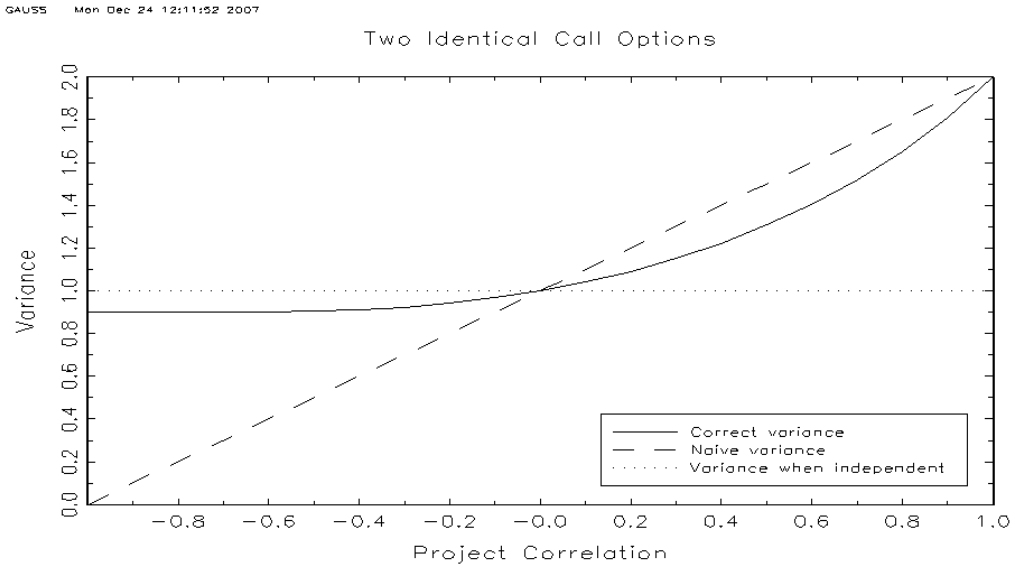
$$\sigma^2_{1\&2} = \sigma^2_1 + \sigma^2_2 + 2\rho\sigma_1\sigma_2 \tag{8}$$

The difference lies in the interpretation of the correlation coefficient ρ (the horizontal line σ^2_0 illustrates the degenerate case where ρ is zero), which measures the correlation between projects. In case of the naively calculated variance $\tilde{\sigma}^2_{pf}$, the projects are correlated one-to-one with the projects' market values and ρ is a constant. In case of the correct variance σ^2_{pf}, however, co-movement between real option projects is a function of market value *and* the probability that a project is terminated [11] . A manager that doesn't recognize real option characteristics would end up calculating risk naively, and Figure 2 illustrates how naively calculated risk may differ from correctly simulated risk .

In the Figure, the naive portfolio variance at $\rho = 0$ equals the simulated variance of the portfolio and the separate options. We also see that both $\tilde{\sigma}^2_{pf}$ and σ^2_{pf} are reduced when projects are less then perfectly positively correlated, and that two perfectly positively correlated projects have a variance of 200% compared to σ^2_0, as proven in Appendix A. When the projects are negatively correlated, both $\tilde{\sigma}^2_{pf}$ and σ^2_{pf} are less then σ^2_0. These are all diversification effects in line with the theory posed by Markovitz.

[11] This fact has also been used in the theoretical derivations of our results in Appendix A.

Figure 2. Simulation Results for Two Identical Investment Opportunities
Each trial generates two random samples y_1 and y_2 and, subsequently, two option values. Simultaneously, option values are calculated for increasing correlation increments, ranging from 1.0 to + 1.0. Apart from the risk-free rate, all elements are assumed to follow their own, distinctive process. All other parameters are set as follows:
Number of Trials: $n = 50,000$
Number of Options: $i = 2$
Project Market Value: $V_1 = V_2 = 20$
Investment: $X_1 = X_2 = 25$
Volatility: $\sigma_1 = \sigma_2 = 5$
Time to Maturity: $T_1 = T_2 = 18$ months
Risk-free rate: $r = 5\%$



The 'convexity effect', however, limits the most severe value drops but leaves all positive development intact, so that project payoffs are non-linear and the value distribution becomes skewed. Figure 2 and Appendix A both show that when the value dynamics of individual projects can no longer be offset, naively applying Markowitz diversification may lead to significant miscalculations of risk. This is caused by the interaction between diversification and convexity effects, which has both positive and negative consequences. When projects are positively correlated, the cushioning of convexity enhances diversification and overall risk becomes lower than under Markowitz. But when the projects are negatively correlated, the cushioning of convexity hampers the diversification

effect, leading to a less effective hedge. As a consequence, options are more complex instruments for diversification than stock. In terms of the effect that correlation has on risk, the sensitivity of unconditional risk to changes in correlation is generally smaller than for unconditional risk, up to a correlation of about $\rho = 0.70$: especially for negatively correlated projects, diversification is hardly changing the portfolio's risk. Stated more precisely, the variance of a conditionally staged portfolio is compressed towards the cumulative variance for two independent options. The range of a conditionally staged portfolio is smaller than the range of an unconditional portfolio, but the minimum is higher than the unconditional portfolio's minimum. We can formulate the following hypotheses:

H1: Under positive correlation, conditionally staged projects diversify risk better than unconditional projects.

H2: Under negative correlation, unconditional projects diversify risk better than conditionally staged projects.

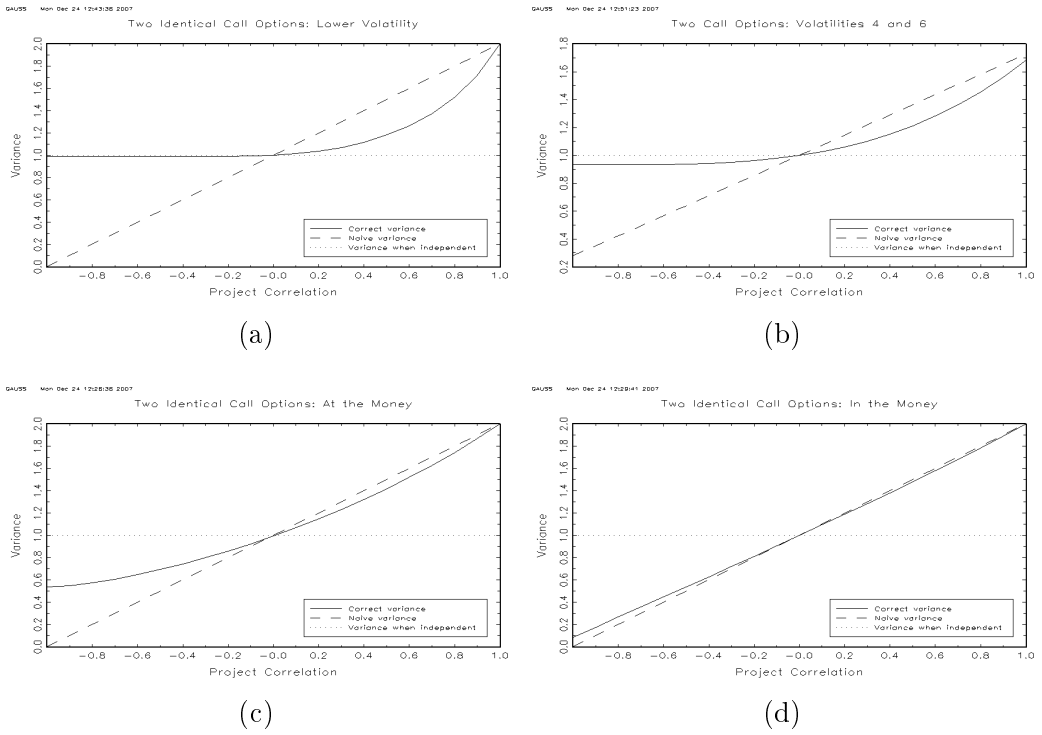
3.3 Robustness Analysis and General Applicability

The base case (Figure 2) shows what happens when two simple and identical options are out of the money: the investment hasn't been recovered yet. This setting is typical for many R&D projects. Figures 3a-d show results of simulated options that have a lower volatility (Figure 3a), a different volatility (Figure 3b), are at the money (Figure 3c) or in the money (Figure 3d). In all these situations, the convexity-effect persists. In Figure (a), we halve the volatility so that the project is not in the money until the value equals $\mu + 2\sigma$. In R&D, this means that the project is not continued in about 97.5% of the

cases and hardly any of these projects is available for risk diversification. As a consequence, the diversification effect is almost absent and all we see is the convexity effect: we might just as well not diversify at all. As a less extreme case, when volatilities differ, Figure (b) shows that portfolio risk is less sensitive to changes in correlation than in Figure 2 and diversification is still quite ineffective. Please note the unit change on the y-axis, indicating that in this case, zero variance can not be achieved by naive calculation either. When the moneyness increases in Figure (c) and (d), the curves move towards the straight line and our results become less distinct. This reflects the familiar fact that options that are deeply in the money will behave similarly to the underlying stock. As a consequence, the convexity effect becomes less pronounced and the diversification effect starts to dominate. In R&D, this means that if the value of the project is much higher then its costs, conditional staging doesn't make a large difference because the project will be exercised anyway.

A few general remarks are in order here. Many projects are funded by multiple finance or subsidy rounds and our simple calls represent the last phase. The pharmaceutical industry, for example, is typically characterized by six stages of development. This means that the condition of completing the sixth phase is conditional upon completion of the fifth phase, which is conditional on the fourth phase, etcetera. These more realistic features can easily be modeled by using compound options in the simulation. In the compounded case, we are stacking 'effect on effect'. This is not demonstrated here, because such simulation results are highly dependent on the success of entering the next round: such arbitrarily chosen input parameters (especially for several stages) will have a critical influence on the portfolio variance and conceal the convexity effect. Compound options can easily be put to practice by means of Cassimon et al. (2004), who have developed a closed-form model for the suc-

Figure 3. Sensitivity Analysis of Simulation Results
Figure (a) shows a volatility of 2.5 instead of 5 for both options.
Figure (b) shows a volatility of 4 and 6 for each instead of 5 for both options.
Figure (c) shows a project value of 25 instead of 20.
Figure (d) shows a project value of 30 instead of 20.
All other option parameters are identical to the base case in Figure 2.



cessive phases from R&D to commercialization. Likewise, simulation makes it straightforward to implement other realistic features such as uncertain costs or time-to-completion. That, however, would also drive us away from the essential portfolio diversification problem.

For ease of exposition, we have limited the analysis to the smallest portfolio possible, a portfolio of two projects. The effect is also observable when we increase the number of assets. If we introduce a third asset and keep the step size fixed at 0.10, for example, then 21 correlated samples are ranked similarly for every random variable. So for the 3-variable case we have a grid of 21 correlation points between variable 1 and 2, 21 between 1 and 3 and 21 between 2 and 3. Appendix B describes how to develop the simulation

procedure for three and more projects by constructing a consistent correlation structure [12] .

3.4 Implications

The implications of our results can be readily applied in any research policy that concerns simultaneous development. While various applications may illustrate the use of our findings, we give an example that originates from the pharmaceutical industry. In this sector, many small firms succesfully focus on a few drugs, rather than become part of a portfolio of a large, diversified company. Why is risk diversification not necessary for small research ventures to be successful in such risky business? One argument would be that in the early stages of development, economies of scale (e.g. in marketing) are not feasible yet. Another would be that the R&D process is differently organized for small ventures than for big companies. Our results give an additional argument for this behavior: a strong focus only marginally increases the risk of the portfolio while it may strongly contribute to non-diversification criteria (such as synergies and spillovers) and preserve the upward potential. We also provide an argument in favor of active portfolio management: as portfolios need restructuring when projects evolve and become less risky, the venture may be sold to a diversified company.

If conditionally staged projects are positively correlated, their combined value is less volatile than standard portfolio theory might suggest. Portfolio risk is

[12] At the same time, the number of possible correlations is smaller than 63. If, for instance, two projects c_1 and c_2 have a negative correlation of 0.99, the third cannot be highly correlated with both at the same time. In this three-variable case, the correlation between c_1 and c_2 and a third, single option can only be defined on the complete interval [-1, 1] when the correlation of the two projects c_1 and c_2 is held constant at $\rho = 0$.

likely to be overestimated because the diversification effect is cushioned by the convex nature of options. In terms of diversification, these projects are good candidates for portfolio selection. If, conversely, drug development projects are negatively correlated and the uncertainty is high enough to let progress be conditionally staged, then the cushioning of convexity causes diversification to be less effective than would be expected from Markowitz. As time progresses, the results of these R&D programs improve and become less uncertain, the cushioning disappears and the projects will behave more stock-like. In these later stages, diversification becomes more important in portfolio selection as the risk becomes more sensitive to changes in correlation.

It may be useful to provide examples of positively and negatively correlated risk as well. Positively correlated risk can partly be ascribed to non-diversifiable market risk. Another part may be ascribed to the medical context, where positively correlated projects may represent two or more drug development programs projects that will lead to 'complementary treatment' of illness: a first example is the case for the treatment of HIV, where (due to mutations) any mono-therapy is not able to suppress an HIV-infection and a combination of three drugs is prescribed. When the side effects of one drug become less severe, or if the effectiveness of one drug improves, the value of the other two drugs will increase as well, because the quality of the treatment increases. As a second example, we can think of drugs that treat disorders that are strongly related such as lung cancer and cardiovascular diseases. Often, both are the result of a common cause such as an unhealthy lifestyle. When patients can be treated for one disease, the patient will live longer and the odds increase that he will suffer from the second disease. Ironically, this is good news for investors as the market value of both drugs increases. An example of negatively correlated risk lies in two drug development programs that are substitutes:

if the value of one program goes up due to a major discovery, the value of the other project automatically goes down (for instance, when two development programs aim to cure similar diseases). The risk of negatively correlated projects is only marginally lower in a portfolio than for independent projects. Therefore, although non-diversifcation arguments may provide good reason to combine these projects, risk reduction isn't one of them. Until the projects mature and risk has been diminished, negatively correlated risky projects are less attractive portfolio candidates for risk management.

We consider the pharmaceutical industry to be a well-chosen example for its active portfolio management also. It is evident that corporate risk diminishes as new ventures reach maturity. In Figure 1, our framework indicates that ventures first behave as the curvature, and later behave as the straight, dotted line. The gentle slope of the curve shows that although the risk of positively correlated ventures is still higher than the risk of negatively correlated ventures, the difference doesn't matter as much as standard portfolio theory predicts. Therefore, structuring a portfolio to minimize variance is not as important in the early stages. When ventures mature, however, diversification becomes more important and the risk characteristics of positively and negatively correlated ventures become more pronounced. It may be wise to sell positively correlated ventures in this stage.

4 Conclusion and Future Research Directions

In this article we have shown that the presence of conditional staging in R&D invalidates diversification arguments when a portfolio is constructed. Under negative correlation, emphasis should be placed on other (non-diversification)

arguments when constructing a portfolio whereas under positive correlation, the advantages of diversification are larger than one may expect from Markowitz diversification. We have also demonstrated that due to the convexity of high-risk projects, the sensitivity of portfolio risk to correlation is smaller for high-risk projects than for low-risk projects.

Implementation of our model is straightforward, and shows that the difference in risk between high-risk and low-risk projects can be quite substantial: for two negatively correlated risky projects of about $\rho = -0.5$, the uncertainty is reduced by only $10\%/50\% = 20\%$ as compared to low-risk uncertainty reduction. For $\rho = +0.5$, the uncertainty is increased by only $30\%/50\% = 60\%$ as compared to low-risk uncertainty. These differences can easily become more dramatic (in extreme cases, diversification becomes impossible), and our findings are robust to changes in the parameter structure of the model. We have provided examples to show why this is important for the R&D portfolio of a drug developer.

Some extensions to the model can make it more suitable to analyze portfolio risk under more specific circumstances. One can easily construct a portfolio with projects that differ in volatility, time to maturity and moneyness. We have explained the possibility of compounding options when additional parameters (such as success probabilities) are known. Using a provided algorithm, it is easy to extend the analysis to a large portfolio, with each project having its own distinct features such as the required investment outlay, estimated date of completion and volatility of market value. The simulation procedure remains the same for several underlying stochastic processes and may include other case-specific peculiarities such as mean reversion, barriers or autocorrelation. It is also possible to account for synergies on the cost side. Future research may

hence yield similar results as ours, but from real-life data. For expositional purposes, however, all these extensions would unnecessarily complicate our argument.

An important implication that follows from our work is that, when evaluating the risk of a portfolio of risky R&D opportunities, it is not sufficient to merely examine the risk-return properties between projects: it is also important to determine the presence of staged conditionality before drawing conclusions on how appropriate a project is for reducing the risk of the portfolio. When additional information is available on project parameters to tailor the model to a specific problem, our framework could also be helpful in the formulation and assessment of research and development policy by public and private parties.

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Appendix A: Explicit Derivation of Main Results

To examine the variance of a risky R&D portfolio more closely, an analytical treatment of our theoretical framework will convey what happens when the correlation is perfectly positive, negative or absent. Because of the nature of options (i.e., the max operator), the variance of a single call option consists of two properly weighted variances, namely one variance in case the call value is positive – which we will denote by $Var(c^+)$ – and one for the case the outcome is zero:

$$Var(\max[V - I, 0]) = w_1 Var(V - I) + w_2 Var(0) = w_1 Var(c^+) \qquad (9)$$

where w_1 and w_2 are the appropriate weights. The key to an analytical derivation of the variances is recognizing the outcome possibilities that exist in each of the three correlation scenarios, and construct a single variance from there, using a variance decomposition formula that is defined as:

$$Var(X) = E[Var(X|Y)] + Var(E[X|Y]) \qquad (10)$$

We will consider a portfolio of two simple investment opportunities (calls) that are exactly equal two each other. Both require an investment X that is, by assumption, equal to the expected value of the project (for ease of notation, we drop the subscript i that we introduced in Section 3.1):

$$X_1 = X_2 = X = E[V_T] \qquad (11)$$

As a consequence, for at the money options, each call will be distributed

around $E[V_T]$(again, we drop the subscript i):

$$\Pr(V_T > X | X = E[V_T]) = \Pr(\varepsilon > 0) = 0.5; \varepsilon \sim N(0,1) \tag{12}$$

Furthermore, since both calls are identical, we know that the probability of being in the money is equal for both calls i, j:

$$\Pr(V_{i,T} > X) = \Pr(V_{j,T} > X) \tag{13}$$

The cases of perfectly positive, negative or absent correlation differ only in the correlation that exist between two projects, and each will yield a different expression for the portfolio variance, as expressed in terms of the option components' variance in 9.

Perfectly positively correlated projects

For $\rho = 1$, either both calls are in the money or both calls are out of the money. This means that the portfolio consists of two possible outcomes:

$$Pf = (c_1^+ + c_2^+ | V_1 > X, V_2 > X) + (0 | V_1 < X, V_2 < X)$$

Because of equation 12 and equation 13, each outcome is equally likely. In this case (denoting the positive part of the portfolio by pf^+ and the negative by pf^-), the variance composites on the right-hand side are:

$$\begin{aligned} Var_{pf^+} &= Var(2c^+ | V > X) = 4 \times Var(c^+ | V > X) \\ Var_{pf^-} &= 0 \end{aligned}$$

Furthermore, we know that $E[pf^+] = 2E[c^+]$ since both projects are identical. From equation 10, it follows that the portfolio variance of a portfolio is:

$$\begin{aligned} Var(pf|\rho = 1) &= \frac{4Var(c^+) + 0}{2} + \frac{(2E[c^+] - E[c^+])^2 + (0 - E[c^+])^2}{2} \\ &= 2 \times Var(c^+) + E[c^+]^2 \end{aligned}$$

Perfectly independent projects

For $\rho = 0$, we know from equation 12 and equation 13that each option can be in the money or out of the money with equal probability. In this case, we can therefore distinguish 4 possible outcomes :

$$\begin{aligned} Pf = &(V_1 - X|V_1 > X, V_2 < X) \\ &+ (V_2 - X|V_1 < X, V_2 > X) \\ &+ (V_1 - X + V_2 - X|V_1 > X, V_2 > X) \\ &+ (0|V_1 < X, V_2 < X) \end{aligned}$$

The variance of the first two terms on the right hand side is equal to $Var(c^+)$, and the expected value for both is $E[c^+]$. Since the non-linear payoff is accounted for in the last term, we can use Markowitz to find the variance of the third term, which is simply the sum of the variances $Var(c_1^+)$ and $Var(c_2^+)$ because $\rho = 0$. Furthermore, we know that the expected value of this term equals the sum of the expected values $E[c_1^+]$and $E[c_2^+]$. It follows from equation 10 that

$$\begin{aligned} Var(Pf|\rho = 0) = &\frac{Var(c^+) + Var(c^+) + 2var(c^+) + 0}{4} \\ &+ \frac{0 + 0 + (2E[c^+] - E[c^+])^2 + (0 - E[c^+])^2}{4} \\ = &Var(c^+) + 0.5(E[c^+])^2 \end{aligned}$$

This is exactly half of the variance found at $\rho = +1$, a finding that corresponds with the simulation results.

Perfectly negatively correlated projects

For $\rho = -1$ and at the money options, we know that either one call or the other is in the money. But because both projects can never jointly be in- or out of the money at $\rho = -1$, this simply means that the variance is equal to either the variance of one call, or that of the other. More precisely, we can state that:

$$\begin{aligned} Pf &= (c_1^+ + 0 | V_1 > X, V_2 < X) + (0 + c_2^+ | V_1 < X, V_2 > X) \\ &= c_1^+ = c_2^+ = c^+. \end{aligned}$$

We can write the last line because the calls are identical under the given conditions. It follows directly that we can write:

$$Var(Pf | \rho = -1) = Var(c^+)$$

This demonstrates why in our results, the variance of a perfectly negatively correlated portfolio doesn't go to 0% in the limit but is of a magnitude between zero and the variance at $\rho = 0$. Indeed, diversification under these circumstances does not permit risk to be diversified away.

Appendix B: How to Generate Random Samples from a Multivariate Normal Distribution

In case a third stock enters our model, a third sample is drawn; ρ_{13} and ρ_{23} need to be defined in such a manner that the variances and covariance are consistent, for instance, if asset 1 and asset 2 strongly move together as well as asset 1 and 3 (i.e., the correlations ρ_{12} and ρ_{13} are highly positive), then the dynamics of asset 2 and 3 need to be positively related to some extent (i.e., ρ_{23} needs to have a high positive value) as well. If we require 3 correlated samples from normal distributions, the required samples are defined as follows:

$$\varepsilon_1 = \alpha_{11} x_1 \tag{14}$$
$$\varepsilon_2 = \alpha_{21} x_1 + \alpha_{22} x_1 \tag{15}$$
$$\varepsilon_3 = \alpha_{31} x_1 + \alpha_{32} x_1 + \alpha_{33} x_1$$

The Cholesky decomposition procedure sets $\alpha_{11} = 1$ and requires α_{21} to be chose such that $\alpha_{21}\alpha_{11} = \rho_{21}$ and $\alpha_{21}^2 + \alpha_{22}^2 = 1$. This yields

$$\alpha_{21} = \rho_{21} \tag{16}$$

and

$$\alpha_{22} = \sqrt{1 - \rho_{21}^2}. \tag{17}$$

For the third sample, α_{31} is to be chosen such that $\alpha_{31}\alpha_{11} = \rho_{31}$, yielding $\alpha_{31} = \rho_{31}$. Then α_{32} is to be chosen such that

$$\alpha_{31}\alpha_{21} + \alpha_{32}\alpha_{22} = \rho_{32}, \tag{18}$$

leading to

$$\alpha_{32} = \frac{\rho_{32} - \rho_{12}\rho_{13}}{\sqrt{1 - \rho_{12}^2}}. \tag{19}$$

We conclude by the requirement that

$$\alpha_{31}^2 + \alpha_{32}^2 + \alpha_{33}^2 = 1, \tag{20}$$

leading to

$$\alpha_{33} = \sqrt{1 - \rho_{13}^2 - (\frac{\rho_{23} - \rho_{12}^2\rho_{13}^2}{\sqrt{1 - \rho_{12}^2}})^2}. \tag{21}$$

We can simply generalize this case to n by expanding the Choleski matrix in equation 15, for example to

$$\varepsilon_4 = \alpha_{41}x_1 + \alpha_{42}x_2 + \alpha_{43}x_3 + \alpha_{44}x_4 \tag{22}$$

and repeat this procedure. But correlations need to be chosen with more and more care as the number of projects increases. In case of 2 projects, the restriction imposed by (B2) implies that ρ_{12} must be smaller than 1. Although not very demanding in the two-variable case, the requirements above pose more restrictions on the correlated projects for every project that enters the simulation. We initially consider a single drug. If we want to simulate two additional projects that both are correlated to this drug $\rho_{12} = \rho_{13} = -0.9$, then these projects need to be positively correlated. More specifically, if we let the third variable enter the simulation, it must satisfy:

$$\alpha_{31}^2 + \alpha_{32}^2 + \alpha_{33}^2 = 1 \tag{23}$$

or

$$\alpha_{33}^2 = \sqrt{1 - \alpha_{31}^2 - \alpha_{32}^2} = \sqrt{1 - 0.9^2 - \alpha_{32}^2} > 0. \tag{24}$$

Hence, the Choleski-variable α_{32}^2 must not be larger than (1 - 0.81 =) 0.19 and

$$\sqrt{0.19} \leqq \alpha_{32} \leqq \sqrt{0.19}. \tag{25}$$

Using this condition in the other requirement 18, we find the following range:

$$\rho_{23} \leq 0.90 \times 0.90 + 0.19 \times 0.19 = 0.88$$
$$\rho_{23} \geq 0.90 \times 0.90 - 0.19 \times 0.19 = 0.62.$$

If a fourth project enters the story and $\rho_{14} = \rho_{12} = \rho_{13} = -0.9$, it is required that

$$\alpha_{44}^2 = \sqrt{1 - \alpha_{41}^2 - \alpha_{42}^2 - \alpha_{43}^2} = \sqrt{1 - 0.9^2 - \alpha_{42}^2 - \alpha_{43}^2} > 0$$

and, similarly to equation 25, that

$$-\alpha_{22} \leq \alpha_{42} + \alpha_{43} \leq \alpha_{22},$$

meaning that $\alpha_{42} + \alpha_{43}$ are subject to the same constrant as was α_{32}. So any newly entering simulation variable is subject to all previous constraints plus 1. For instance, if we choose $\rho_{42} = \rho_{32}$(so $\alpha_{42} = \alpha_{32}$ and $\alpha_{41}, \alpha_{42}, \alpha_{43} = \alpha_{31}, \alpha_{32}, \alpha_{33}$), it must be true that

$$\alpha_{44} = \sqrt{1 - \alpha_{41}^2 - \alpha_{42}^2 - \alpha_{43}^2} = \sqrt{1 - 0.81 - 0.19 - \alpha_{43}^2} > 0$$

and the fourth project needs to be uncorrelated with the others for consistency.